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The Impact of Using BI-RADS with Voting Classifier Fusion for Early Detection of Breast Cancer

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Abstract

Breast cancer is one of the leading causes of death among women worldwide. The chances of a patient's cure depend significantly on the stage of cancer at the time of diagnosis. Currently, the accuracy of Computer Aided Diagnosis System (CADs) using Mammography BI-RADS is approximately 80%, highlighting the need for further enhancement. The most commonly used classifiers include Multilayer Feed Forward Neural Network (MFFNN), Liner Discriminant Analysis (LDA), Support Vector Machine (SVM) and k-Nearest Neighbour (KNN). One of the key factors affecting the performance of CADs is the choice of classifier, as different classifiers may produce varying of misclassified samples, leading to differences in classification accuracy. In this study, 191 samples were used as an input for four classifiers: MFFNN, LDA with leave one out cross validation (LOOCV), SVM-LOOCV and KNN-LOOCV. To minimize the number of missclassified samples, this study employed the majority voting classifier fusion algorithm, which combines the results of the four classifiers to obtain a more robust decision. By comparing the accuracy of the majority voting classifier fusion algorithm with the best results obtained by individual classifier (KNN), the results showed that the voting classifier fusion algorithm outperformed KNN, achieving classification accuracies of 84.8% and 83.7%, respectively.

Keywords: *Classifier Fusion, Artificial Neural Networks, Breast Cancer, SVM, Mammography.*

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1 Introduction

Breast cancer is considered as the second most common cause of cancer related deaths among women. In 2018, 25.4% of cancer cases were reported as breast cancer [1]. Improvements in breast cancer survival rate are strongly linked to the stage of cancer at the time of diagnosis. Patients diagnosed at an early stage have a significantly higher chance of survival. There are several non-surgical techniques used for breast cancer diagnosis including MRI, Ultrasound, CT scans, and digital mammography. Among these, digital mammography is considered the most commonly used technique for detecting non-palpable breast cancer. This technique is safe and accurate; it is an X-ray photograph of the breast and has been in use for about 30 years [2].

Mammograms are carefully observed and analyzed to ensure an accurate diagnosis. The process begins with identifying any changes in breast tissues, known as Regions of Interest (ROIs), such as microcalcifications or masses. These changes are among the most significant findings in mammogram images. If a radiologist notices such a region, they decide whether it appears normal or not. If the area cannot be clearly distinguished as normal, it is classified as suspicious and requires further examination. Suspicious areas generally fall into three categories: asymmetric density, architectural distortion, and calcifications [3].

The Breast Imaging Reporting & Data System (BI-RADS) is a standard reporting system that used to describe the mammography images in a way that makes the follow up protocol easier. The report describes mass in terms of mass shape, mass margin, subtlety, size, calcification and patient age.BI-RADS then is used to classify the mass into six categories ranged from negative to known biopsy-proven malignant [3].

Microcalcifications and masses are two important findings in mammograms. Masses are generally characterized by their shapes, sizes, and margins. The shape of the mass can be described as round, oval, lobular, or irregular. These features help radiologist in differentiating benign form malignant cases. For example, masses with oval or round shapes are more likely to be benign. On the other hand, irregular shapes are most likely to be malignant. Furthermore, the margins can be described as circumscribed, microlobulated, obscured, ill-defined or speculated. Where, ill-defined, microlobulated andspeculated are strong indicators of malignant and need further investigations. Whereas circumscribed masses are more likely to be benign. Similarly, calcifications varying sizes, numbers, morphologies, distributions, and heterogeneities [4, 5]. From these alterations, the radiologist classified the findings to benign or possibly malignant [6, 7]. Despite the high accuracy of the mammogram in diagnosing breast cancer, about 60% of breast biopsies are done for benign cases. This is because the classification of mammographic findings relies on radiologist interpretation, which can be subjective.. In order to enhance the diagnostic accuracy of the mammography imaging computer aided diagnosis system (CADs) have been developed.

2. Related Work

Several studies have been conducted for developing efficient CADs for the early detection of breast cancer. These CADs have been used different classification algorithms. For example, Fuzzy logic and genetic algorithms have been used for classifying the Region of interest (ROI) containing microcalcification as either benign or malignant using a small number of samples. The results showed high sensitivity and low specificity, 100% and 75% respectively [8]. Additionally, Bayesian networks where used for classifying the pathological data of fine-needle aspiration of the breast lesion (FNAB) and achieved 83% classification accuracy. Likewise, association rules (AR) and neural network (NN) were used for feature selection and classification of demographical and historical data of patient and achieved about 95% accuracy rate[9]. Moreover, Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM) have been used for building breast cancer CADs and obtained about 95% classification accuracy [10]. Similarly, Least-Squares Minimum Distance and K-Nearest Neighbour (KNN) have been employed for such CADs [9, 11, 12]. The results of these studies showed that appling different classifiers to the same dataset in most cases yielded different results including differences in accuracy, sensitivity, specificity, false positive rates, and false negative rates.

The differences in performance among various mammography-based CADs were not solely attributed to the classifiers used but also to the input features extracted and utilized for building these systems. For example, the arrangement and variation of intensities (gray values) within mammogram images have been used for developing breast cancer CADs,obtaining 83%-74% classification accuracies using different ROI [13]. Additionally, Georgiou et al. [14] and Baeg et al. [15] studied the predictive power of the mass features extracted from the radiologist report (BI_RADS), including shape and boundary, in the early detection of breast cancer. The classification accuracies from these studies were ranged from 70-82%. These studies used simple feature extraction phase from the BI_RADS report. On other hand, several studies have used complex feature extraction approaches. For example, Chan et al. [16] compared the accuracies of three CADs that used three different types of mass features: the first CADs used textural features, the second one used morphological features and, the third one combined both texture and morphological features. The study found that the texture features based CADs were more accurate in the early detection of breast cancer than morphological features based CADs, while the highest accuracy was obtained from the combination of both features CADs. Also, Loizidou, Skouroumouni, Nikolaou and pitris [17] developed an automatic feature extraction and classification for mammography images and obtained 92.6% classification accuracy. Similarly, the geometric features of ROI were extracted and used as input for the CADs, resulting in a classification accuracy of 89% [18]. Despite using a complex phase for feature extraction and selection, these CADs obtained similar performances levels compared to the systems that used simpler feature extraction phase.

By reviewing the results of previous breast cancer CADs, this work found that the diagnostic accuracy of breast cancer CADs depends on two aspects: 1) features used for building CADs and 2) classifier(s) that used for building the CAD System. In terms of feature selection, this study found that features directly extracted from the radiologist report (BI-RADS) are better than the features that need a complex phase for extraction in terms of simplicity and availability. On the other hand, we found the systems that used different classifiers obtained different classification accuracies. This suggests that different classifiers may introduce different misclassifying samples.

The aim of this study is to enhance the diagnostic accuracy of breast cancer CADs using BI-RADS to help save more live. This is can be achieved by minimizing the number of misclassified instances. To do that, this paper combined the results of different classifiers using a voting classifier fusion method [18, 19].

3 Materials and Methodology

In this study, we used 300 samples (150 benign and 150 malignant), all of which were extracted from the Digital Database for Screening Mammography (DDSM). This is a vital resource for digital mammography research. The database was completed in the fall of 1999. It contains 2620 Mammography screening images. All images in the DDSM were collected from four different sources: Massachusetts General Hospital(MGH), Wake Forest University School of Medicine(WFU), Sacred Heart Hospital(SH) and Washington University of St. Louis School of Medicine(WU) [20]. (BI-RADS) classified the lesions into three main categories: mass, microcalcification or both. In most cases (97%), the lesions were either mass or microcalcification but not both. The radiologist carefully investigates the image searching for suspicious areas that may contain either mass or microcalcification. If the mammogram image contains a mass, the radiologist describes the mass using the most commonly used features including: shape, size, margin, density and subtlety of the mass. On the other hand, if the suspicious areas contain microcalcification, the radiologist describes the microcalsification using the following features: calcification type, calcification distribution, density, and subtlety.

Statistically we found 111 cases out of 150 benign cases were masses, while only 39 cases were calcification; about 26% of total benign cases have microcalcification. In contrast, 80 cases out of 150 malignant cases were found to be masses, 61 microcalcification, about 40% have calcification and only 9 cases have both mass and microcalcification. Therefore, building a computer aided diagnosis system using both mass and calcification features would not yield optimal results due to missing values in the dataset, which arise from the difference between the descriptors (features) of mass and microcalcifications. Where, the only shared features between the two findings are subtlety of the lesion, the density of the breast lesions and age. So that, there is a need for building two systems; one based on mass feature and the other based on microcalcification. In this study, we will focus on the effect of using classifier fusion on the performance of the breast cancer CADs using only mass features.

To select the subset of features, we used the frequency analysis to highlight the power of each feature of mass and in discriminating benign from malignant cases as shown in Table1. Accordingly, the frequency analysis of shape and margin of the masses were calculated using 191 samples (masses cases) and for age, subtlety and density we use all samples (300 samples). This is because these features are common to both masses and microcalcification cases.

In this model, the features of 191 samples were used as inputs for four classifiers; Multilayer Feed Foreword Neural Network with back propagation algorithm (MLFFNN), Liner Discriminate Analysis (LDA) K- Nearest Neighbour (KNN), and Support Vector Machine (SVM). The leave one out cross validation (LOOCV) has been applied to LDA, KNN and SVM and 5 fold out cross validation has been used with MFFNN. The sensitivity, specificity and over all accuracy of each classifier are evaluated using ROC curve. Finally, the results of different classifier were combined using voting method (figure 1).

3.1 Support Vector Machine (SVM)

Support vector machine is the process of building a hyperplane between deferent classes in high dimensional data. An SVM represents the vectors of the samples as points in space, where the gap between different classes is as wide as possible. The new object then falls on the same space and labelled with the appropriate class label based on its place[21].

3.2 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis is a statistical classification method that build a hyperplane between different classes by maximizing the variance ratio between and within class[22]. The LDA hyperplane is optimal if and only if covariance matrices of different classes are identical [23].

3.3 MFFNN

Here, we used a MLFFNN with 5 neurons in the input layer, one hidden layer with N neurons and one neuron in the output layer. Determining the optimal number of neurons in the hidden layer (**N**) remains a challenge. To address this, in this, the number was optimized using Self Organizing Map, as described in [28]. After constructing the network structure, Scaled Conjugate Gradient back propagation algorithm with Logistic activation function in the hidden neuron and pure line in the output layer were used for training.

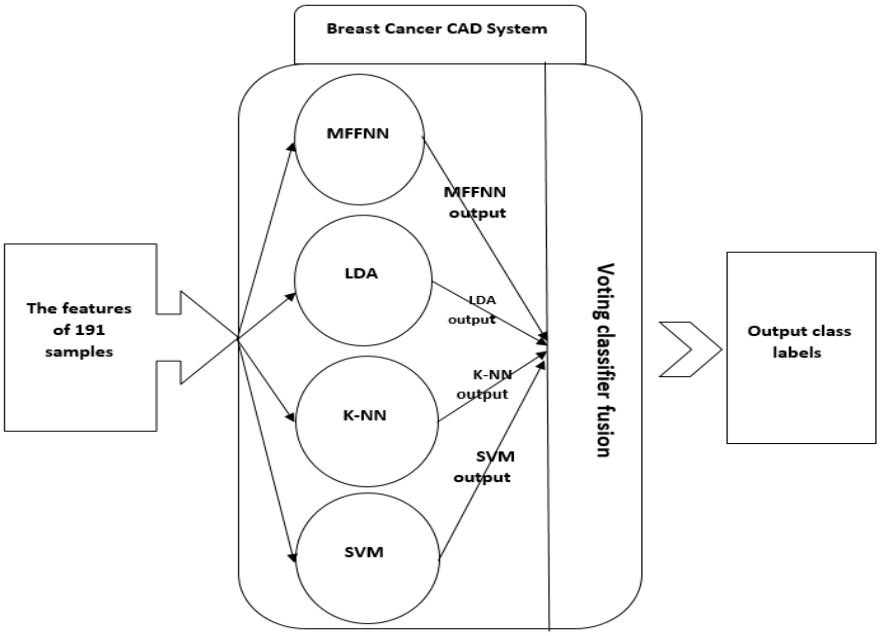


Fig 1: The components of the CAD system including feature selection, classification and classifier fusion.

3.4 KNN

The process of classifying samples in this method depends on the similarity between new sample (unseen sample) and neighbour samples that used for training. In this approach, the training samples are represented as vectors in the feature space and each vector denotes one class. So that KNN is considered as a simplest classifier because there is no actual training phase. When a new sample is introduced, it is mapped into the same feature space classified base on K neighbour vectors in the training sample[24]. To determine the value of k we applied the following steps:

1- Set min = 0; Initial value for accuracy.
2- loop (set I=2 to N), where I is small number of cluster and N is a large number.
   a- Consider K=I, is the best structure.
   b- Use KNN with k=I for classification.
   c- Find current accuracy.
   d- If accuracy of current structure > = min ,set min =current accuracy, Best=I
3- K= Best

3.5 Classifier fusion

Applying deferent classifiers on the same dataset produces deferent miss-classified instances. Classifier fusion is the process of combining the results of multiple classifiers in order to reduce the number of miss-classified instances. Fusion of data can be performed on three levels of abstraction tightly connected with the flow of the classification process[18]: the first one is data level fusion; in this level, the process of combination is done on the raw data of deferent sources. The second one is Intermediate level fusion; this level combines selected features from deferent sources of data. The third one is high level fusion (classifier fusion) that combines decisions from deferent experts. This work focuses on the third type especially, majority voting [25-28]

3.5.1 Improved majority voting classifier fusion

The aim is to minimize the number of misclassified instances. This step is responsible for combining the results of deferent classifiers by applying a voting method[29]. The voting method is applied to combine the results of multiple classifiers using majority of the class label between classifiers. Assume we have n classifiers b_1, b_2, b_3,…,b_n and the model has only 2 different classes{c_1,c_2}. The output of the sample x= [r_1, r_2, r_3… r_n], where, $r \in \{c_1, c_2\}$ ci is the label of class i. For each class, the algorithm finds score vector:

S (ci) = $\{s_1(c_i), s_2(c_i), s_3(c_i), \ldots, s_n(c_i)\}$ where s_j (c_i) is:

$$s_j(c_i) = \begin{cases} 1 \; if \; r_j = c_i \\ 0 \; if \; r_j \neq c_i \end{cases} \quad (1)$$

Next for each class the algorithm calculates score value sv (c_i) as follows:

$$sv(c_i) = \sum_{j=1}^{n} s_j(c_i) \quad (2)$$

Example: suppose there are 6 classifiers and the output labels of the classifiers for input vector x = [c_1, c_1, c_1, c_2, c_1, c_2] and the domain contains two classes {c_1, c_2}. The score vector of c1 s (c1) = {1, 1,1,0,1, 0}. Sv (c1) =4, Sv (c2) =2. The algorithm determines the class label D(xi) for instance xi as follows:

$$\text{D(xi)}=\begin{cases} c_1 \; if \quad sv(c_1) \geq \frac{n}{2}) \\ c_2 \;\; otherwise \end{cases} \quad (3)$$

From the above formula, the algorithm labels the instance xi with c1 in the case where sv(c1) = sv (c2). To solve this problem, this work improves the majority voting method by adding a new voting rule. The new rule selects the classifier with the highest accuracy to be president classifier Prec. Where the president classifier is the classifier with highest accuracy. So, If sv (c1) = sv (c2) then the algorithm labels the instance with Pre_c label $l(Pre_c)$ as follow:

$$\mathrm{D(xi)}=\begin{cases} c_1\ if \quad sv(c_1)\ \phi\ \frac{n}{2}) \\ c_1\ if \quad sv(c_1)=sv(c_2)\ and\ \ l(\Pr e_c)=c_1 \\ c_2\ Otherwise \end{cases} \quad (4)$$

4 Results, Analysis and Discussions

By analyzing the frequencies of the mammography features, we found the patient’s age , mass margin, shape, subtlety and density of the mass are key factors in differentiating benign from malignant cases (Table 1). For example, only 15% of oval shapes masses were malignant. On the other hand, 79% of masses with irregular shapes were found to be malignant. Additionally, we found obscured mass margin is a feature of benign masses where the percentage of malignant cases were found to be 13% of obscured masses. In comparison with masses with speculated margin we found 94% of these masses where malignant. Furthermore, we observed a significant difference in the average age of patients between the benign and malignant groups. The average age of patients in the malignant group was 63 years, compared to 52.5 years in the benign group.

These five features were used as input for the four classifiers; (MFFNN) with 5-fold cross validation, SVM with Leave One Out Cross Validation (LOOCV), LDA with LOOCV and KNN with LOOCV. The output results of each classifier were then evaluated using the most commonly used measures; sensitivity, specificity, FP, FN and accuracy measures.

To find the optimal number of neurons in the hidden layer, this model is started by a network containing 25 neurons, considered as a large number, Then, each neuron in the trained network is represented as a vector using its weights. After that, the SOM is used to divide the neurons into similar groups (clusters). By applying these steps, SOM divided the neurons (25 neurons) into 12 clusters fig 2. According to Samarasinghe [30], the best number of hidden neurons is the number of clusters resulting from SOM. Therefore, a network with 12 neurons in the hidden layer was trained and tested. The neural network obtained 82.72% classification accuracy with 83.75% and 81.98% sensitivity and specificity respectively (Table 2).

The second classifier is KNN, and to apply KNN classifier, we need to find the value of K. To do this, the classifier was trained using different values of K, where we started by a large number (K=50) and we gradually decreased until K=2. After that, we compared the accuracies of different classifiers. The best results were obtained when the value of k was 15 Fig 3. Where, the classifier obtained 83.77% classification accuracy with 81.25%, 85.59%, 19.75% and 13.64%, sensitivity, specificity, false negative and false positive rate respectively Table 2.

Table 1: Frequency analysis of the BI-RADS features, where B represents the number of benign cases, M represents the number of malignant case and M ratio represents the ratio of malignant cases in the specified value of feature.

Feature	Value	Benign	Malignant((M)	M %
Mass shape	Oval	45	8	0.15
	Round	14	6	0.30
	Lobulated	33	8	0.20
	Architectural_distortion	1	10	0.91
	Irregular	13	49	0.79
	Irregular-architectural_distortion	0	2	1
	Focal_asymmetric_density margins	1	1	0.50
Mass margin	Circumscribed	21	4	0.16
	Obscured	65	10	0.13
	Microlobulated	8	2	0.2
	Spiculated	2	29	0.94
	Ill_defined	13	37	0.74
Age	Average	52.6	63	
Subtlety	1-clear	9	15	0.63
	2	25	34	0.57
	3	37	40	0.51
	4	48	33	0.41
	5-diffecult to see	31	28	0.48
Density	1-fat	15	12	0.44
	2	58	74	0.56
	3	47	42	0.47
	4-dense	32	20	0.38

The third classifier was SVM, which achieved 82.72% classification accuracy with the lowest sensitivity value (77.5%) (Table 2). The last classifier was LDA, where the accuracy of the classifier was 83.25 %. By comparing the accuracies of different classifiers, we found that KNN performed the best (Table 2).

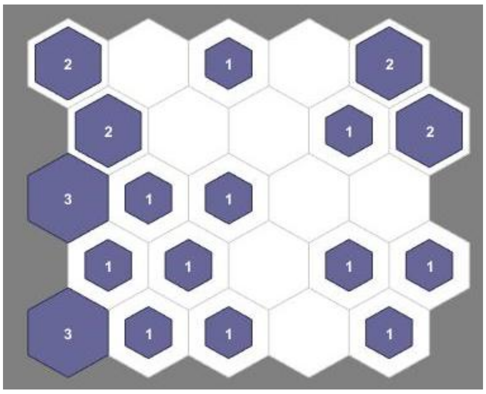


Fig 2: The distribution of the 25 neurons over the SOM showed that, there are 14 overlapped neurons and each overlap can be represented using one neuron. For example, in the bottom right corner, three neurons form a cluster and can be also represented by one neuron.

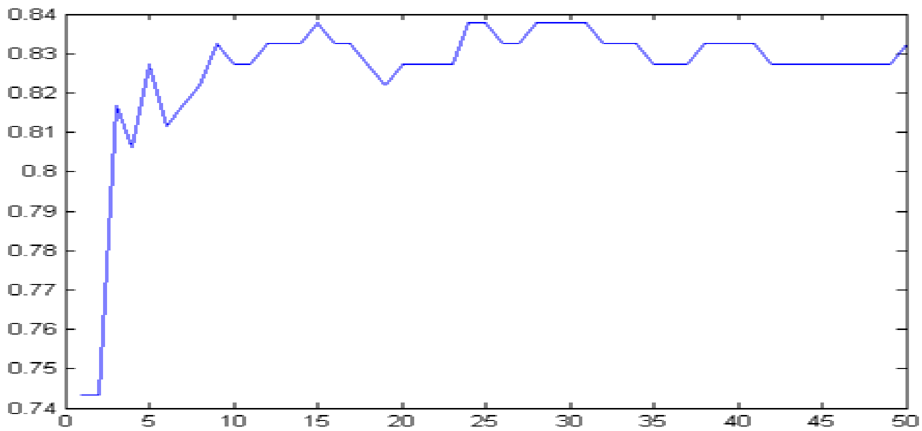


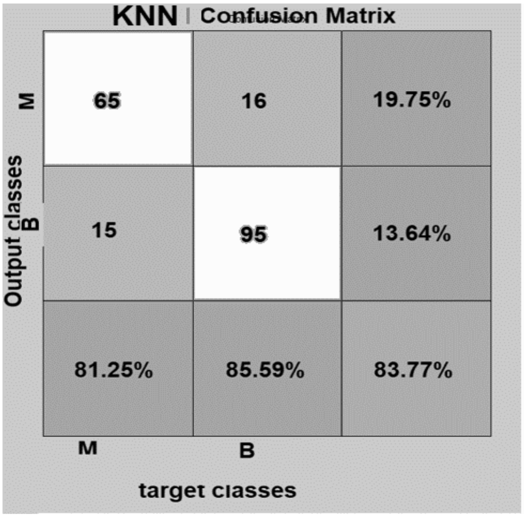
Fig 3: The x-axis represents k value and the y-axis represents the accuracy of the KNN classifier. The best result was obtained using k=15 with 83.77% classification accuracy.

Table 2. The performance measures of the four classifiers (SN- sensitivity, SP-specificity, FN-false negative, FP-False positive and Ac-accuracy).

Classifier	SN%	SP%	Fn %	FP %	Ac
SVM	77.50	86.49	19.48	15.79	82.72
LDA	80.00	85.59	19.75	14.55	83.25
MFFNN	83.75	81.98	22.99	12.50	82.72
KNN	81.25	85.59	19.75	13.64	83.77

Among the various classifiers evaluated, KNN demonstrated the best performance, achieving a sensitivity of 80%, specificity of 85.6%, and accuracy of 83.77%. However, there is still about 16.6% misclassified cases, indicating aneed for more improvement to save more lives. Now, by reviewing the misclassified cases of different classifiers, this work found some misclassified instances were not shared between classifier this means that integrating the results of different classifiers could enhance the overall accuracy. To do that, the improved voting method was applied, as described previously.

The results of the improved classifier fusion showed that, 96 out of 111 benign cases were correctly classified, with 86.4% specificity and 87.27% true negative rate (with FN rate of 12.73%). On the other hand, 66 out of 80 malignant cases were correctly classified with 83.7% sensitivity and 81.48% true positive rate (with FP rate of 18.52%). The overall accuracy of the classifier fusion was 84.82%. By comparing the results obtained by voting classifier fusion and the output results of the best classifier (KNN), this study found that the classifier fusion outperformed KNN (Figure 4).



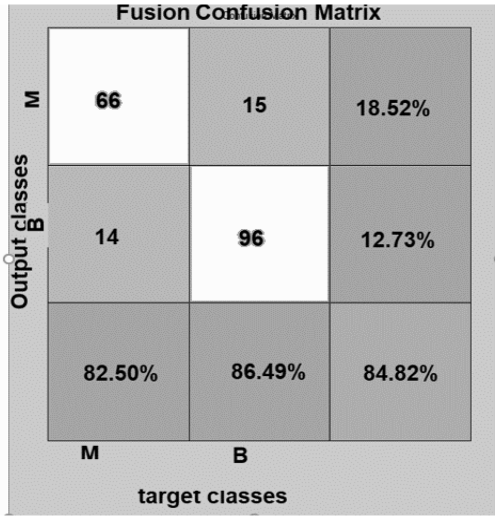


Figure 4: The left matrix is KNN confusion matrix (best individual classifier) and right one is Fusion classifier matrix. The rows represent the output classes and columns represent the target classes, where, M malignant and B benign. The white squares represent the number samples that were correctly classified and the light gray squares represent the number (no percent) of samples that were not correctly classified. The percentages represent FP, FN, Sensitivity, Specificity and accuracy.

6 Conclusion

In this study, 191 samples were used for building an intelligent system for early detection of breast cancer using voting classifier fusion. The goal was to minimize the number of missed classified samples by individual classifier. The results of four classifiers; ANN, SVM, LDA and KNN, were used as an input to the voting classifier fusion. The performance of the individual classifier was compared with the final output of the classifier fusion, and we found the classifier fusion outperform the individual classifiers. In future, a larger dataset will be used for validation.

References

[1] I. A. f. R. o. Cancer. (2018). *Worldwide cancer data*. Available: https://www.wcrf.org/dietandcancer/worldwide-cancer-data/#:~:text=Global%20cancer%20incidence%20in%20women,non%2Dmelanoma%20skin%20cancer).

[2] L. Nicosia, G. Gnocchi, I. Gorini, M. Venturini, F. Fontana, F. Pesapane, *et al.*, "History of Mammography: Analysis of Breast Imaging Diagnostic Achievements over the Last Century," *Healthcare (Basel),* vol. 11, May 30 2023.

[3] t. A. C. o. Radiology. (2023). *Breast Imaging Reporting & Data System (BI-RADS®)*. Available: https://www.acr.org/Clinical-Resources/Reporting-and-Data-Systems/Bi-Rads

[4] P.-H. Chen, E. T. Ghosh, P. J. Slanetz, and R. L. Eisenberg, "Segmental Breast Calcifications," *American Journal of Roentgenology,* vol. 199, pp. W532-W542, 2012/11/01 2012.

[5] A. Al-Yousef and S. Samarasinghe, "Improved Ultrasound Based Computer Aided Diagnosis System for Breast Cancer Incorporating a New Feature of Mass Central Regularity Degree (CRD)." *In: Shanmuganathan S., Samarasinghe S. (eds) Artificial Neural Network Modelling.* vol. Studies in Computational Intelligence, vol 628. Springer, Cham. https://doi.org/10.1007/978-3-319-28495-8_10, 2016.

[6] H. Berment, V. Becette, M. Mohallem, F. Ferreira, and P. Chérel, "Masses in mammography: What are the underlying anatomopathological lesions?," *Diagnostic and Interventional Imaging,* vol. 95, pp. 124-133, 2014/02/01/ 2014.

[7] T. D. Geertse, D. van der Waal, W. Vreuls, E. Tetteroo, L. E. M. Duijm, R. M. Pijnappel, *et al.*, "The dilemma of recalling well-circumscribed masses in a screening population: A narrative literature review and exploration of Dutch screening practice," *Breast,* vol. 69, pp. 431-440, Jun 2023.

[8] M. N. A. Kumar, M. N. A. Kumar, and H. S. Sheshadri, "Computer Aided Detection of Clustered Microcalcification: A Survey," *Curr Med Imaging Rev,* vol. 15, pp. 132-149, 2019.

[9] M. Karabatak and M. C. Ince, "An expert system for detection of breast cancer based on association rules and neural network," *Expert Systems with Applications,* vol. 36, pp. 3465-3469, 2009.

[10] M. O. Adebiyi, M. O. Arowolo, M. D. Mshelia, and O. O. Olugbara, "A Linear Discriminant Analysis and Classification Model for Breast Cancer Diagnosis," *Applied Sciences,* vol. 12, p. 11455, 2022.

[11] G. D. Tourassi, B. Harrawood, S. Singh, J. Y. Lo, and C. E. Floyd, "Evaluation of information-theoretic similarity measures for content-based retrieval and detection of masses in mammograms," *Medical Physics,* vol. 34, pp. 140-150, 2007.

[12] B. Verma, P. McLeod, and A. Klevansky, "A novel soft cluster neural network for the classification of suspicious areas in digital mammograms," *Pattern Recognition,* vol. 42, pp. 1845-1852, 2009.

[13] Y. Lv, X. Chi, B. Sun, S. Lin, and D. Xing, "Diagnostic Value of Quantitative Gray-Scale Analysis of Contrast-Enhanced Spectral Mammography for Benign and Malignant Breast Lesions," *Journal of Computer Assisted Tomography,* vol. 44, 2020.

[14] H. Georgiou, M. Mavroforakis, N. Dimitropoulos, D. Cavouras, and S. Theodoridis, "Multi-scaled morphological features for the characterization of mammographic masses using statistical classification schemes," *Artificial Intelligence in Medicine,* vol. 41, pp. 39-55, 2007.

[15] S. Baeg, A. T. Popov, V. G. Kamat, S. Batman, K. Sivakumar, N. Kehtarnavaz*, et al.*, *Segmentation of mammograms into distinct morphological texture regions*. Los Alamitos: Ieee Computer Soc, 1998.

[16] H. P. Chan, B. Sahiner, K. L. Lam, N. Petrick, M. A. Helvie, M. M. Goodsitt*, et al.*, "Computerized analysis of mammographic microcalcifications in morphological and texture feature spaces," *Medical Physics,* vol. 25, pp. 2007-2019, Oct 1998.

[17] K. Loizidou, G. Skouroumouni, C. Nikolaou, and C. Pitris, "Automatic Breast Mass Segmentation and Classification Using Subtraction of Temporally Sequential Digital Mammograms," *IEEE Journal of Translational Engineering in Health and Medicine,* vol. 10, pp. 1-11, 2022.

[18] D. R. a. B. Gabrys, "An Overview of Classifier Fusion Methods," presented at the Computing and Information Systems, 2000.

[19] A. Carè, M. C. Campi, F. A. Ramponi, S. Garatti, and A. T. J. R. Cobbenhagen, "A study on majority-voting classifiers with guarantees on the probability of error∗∗Roy Cobbenhagen was supported by “Toeslag voor Topconsortia voor Kennis en Innovatie” (TKI HTSM) from the Ministry of Economic Affairs, the Netherlands," *IFAC-PapersOnLine,* vol. 53, pp. 1013-1018, 2020/01/01/ 2020.

[20] K. Bowyer, D. Kopans, W. P. Kegelmeyer, R. Moore, M. Sallam, K. Chang, *et al.*, "The digital database for screening mammography," in *Digital Mammography '96*. vol. 1119, K. Doi, M. L. Giger, R. M. Nishikawa, and R. A. Schmidt, Eds., ed Amsterdam: Elsevier Science Publ B V, 1996, pp. 431-434.

[21] M. N. Murty and V. S. Devi, "Support Vector Machines," in *Pattern Recognition: An Algorithmic Approach*, M. N. Murty and V. S. Devi, Eds., ed London: Springer London, 2011, pp. 147-187.

[22] A. J. Izenman, "Linear Discriminant Analysis," in *Modern Multivariate Statistical Techniques: Regression, Classification, and Manifold Learning*, A. J. Izenman, Ed., ed New York, NY: Springer New York, 2008, pp. 237-280.

[23] I. Gokcen and J. Peng, "Comparing Linear Discriminant Analysis and Support Vector Machines," in *Advances in Information Systems*. vol. 2457, T. Yakhno, Ed., ed Berlin: Springer-Verlag Berlin, 2002, pp. 104-113.

[24] O. Kramer, "K-Nearest Neighbors," in *Dimensionality Reduction with Unsupervised Nearest Neighbors*, O. Kramer, Ed., ed Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 13-23.
[25] Z. Ding, R. Leslie, and J. Van Veen, "Wide area integrated maritime surveillance: Bias phenomenon and compensation for latitude/longitude transformations," in *Signal and Data Processing of Small Targets 2003*. vol. 5204, O. E. Drummond, Ed., ed Bellingham: Spie-Int Soc Optical Engineering, 2003, pp. 360-373.
[26] J. C. Bezdek, M. R. Pal, J. Keller, and R. Krisnapuram, *Fuzzy Models and Algorithms for Pattern Recognition and Image Processing*: Kluwer Academic Publishers, 1999.
[27] T. K. Ho, J. J. Hull, and S. N. Srihari, "Decision Combination in Multiple Classifier Systems," *IEEE Trans. Pattern Anal. Mach. Intell.,* vol. 16, pp. 66-75, 1994.
[28] M. I. Jordan and R. A. Jacobs, "Hierarchical mixtures of experts and the EM algorithm," *Neural Comput.,* vol. 6, pp. 181-214, 1994.
[29] W. Li, J. Hou, and L. Yin, "A classifier fusion method based on classifier accuracy," in *2014 International Conference on Mechatronics and Control (ICMC)*, 2014, pp. 2119-2122.
[30] S. samarasinghe, "neural networks for water system analysis:from fundamentals to complex pattern recognition," presented at the Hydrocomplexity:New Tools for Solving Wicked Water Problems, Paris, 2010.

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